THREE-DIMENSIONAL PERMEABILITY MEASUREMENT USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Introduction/ Motivation

The permeability of engineering textiles is direction-dependent and typically expressed by the in- and out-of-plane permeability as well as the orientation of the in-plane permeability. Various approaches have been developed for permeability measurement [1]. The recently published ISO 4410:2023, the first standard on permeability measurement in the context of Liquid Composite molding, focusses on in-plane permeability determined by set-ups based on unsaturated linear (1D) and radial (2D) flow [2]. Out-of-plane permeability still undergoes standardization and is most commonly measured with saturated linear flow [3]. A main advantage of these rather simple flow conditions is that it is comparably easy to derive the permeability, using corresponding algorithms. The main disadvantage is of course the number of tests required to determine the complete permeability tensor.

Instead of measuring the permeability in different measurements, the full permeability tensor can be computed from measurements with a three-dimensional (3D) flow front progression [4]. The problem here is, that the analytical solution is only applicable to flows with a half-ellipsoidal flow front, originating from a central injection point. This again requires a quite thick textile stack so that a decent sized half-ellipsoid has formed before the flow front touches the upper plate. Furthermore, the assumption of a point source is not valid in experimental measurements.

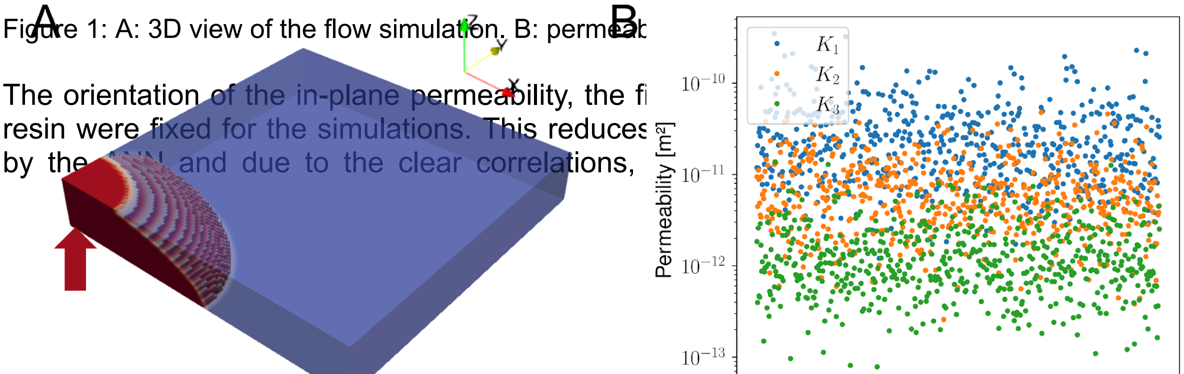
This study presents a new approach to derive permeability from 3D flow. Here, unsaturated 3D radial flow measurements are performed, with the flow front not only touching the upper wall, but purposely forming a second ellipse on this surface. Because the flow cannot be described analytically, an artificial neural network (ANN) is trained with numerical simulations and is used afterwards to compute the permeability from the experiments.

Methods

The permeability test rig is virtually represented and implemented into a finite volume (FV) model to simulate the resin flow in the textile preform. Because of the symmetry of the flow front, a quarter disc model was used to reduce the numerical effort (cf. figure 1A). The simulations are done with the solver anisoImpesFoam [5], which is a two-phase flow solver for OpenFOAM. The solver was validated by the analytical solution from Nedanov et al. [4], and a mesh convergence study was performed. To generate the training data, the permeability values K_1 K_1, K_2 K_2 and K_3 K_3 were individually varied (cf. figure 1B). The mean values are $K_1 = 3.08 \cdot 10^{-11}$ $K_1 = 3.08 \cdot 10^{-11}$ m², $K_2 = 7.76 \cdot 10^{-12}$ $K_2 = 7.76 \cdot 10^{-12}$ m² and $K_3 = 1.55 \cdot 10^{-12}$ $K_3 = 1.55 \cdot 10^{-12}$ m², which are typical values for engineering textiles.

Figure 1: A: 3D view of the flow simulation, B: permeab

The orientation of the in-plane permeability, the fi he
resin were fixed for the simulations. This reduces ed
by the ANN and due to the clear correlations, he



permeability can be easily corrected afterwards. In total 575 simulations were performed, which were used for training, testing and validation. A maximum of 60 % of all simulations were used for the training.

A fully connected neural network (FCNN) is used to compute the permeability values from the experiments. To compute the permeability value from unsaturated measurements, the FCNN needs the flow front progression over time as input data. The flow front on the top and bottom of the laminate can be tracked visually during measurements. The flow in thickness direction cannot be tracked directly. Therefore, the sizes of the ellipses (main axes) on the top and bottom of the flow front are given to the FCNN at different time steps. For ten time steps, the number of input nodes would be 50: $(x_t, y_t, x_b, y_b, t)_i$. The time steps are selected randomly for each experiment in predefined intervals. With this, the simulations can be used multiple times for training (data augmentation). For the output layer, two variants are used: 1) one-node for one permeability value and 2) three-nodes for all three permeability values. For the first variant, three different FCNNs are necessary. The hyperparameters (number of hidden layers, nodes in the hidden layers, etc.) were optimised by Keras Tuner. The loss was computed by the mean absolute percentage error (MAPE).

Results

During the training and testing phase, the influence of the number of training data and the number of training epochs on the quality of the estimation was investigated. The number of training data was changed between 60 and 345 simulations. The training MAPE was around 1 % for all cases. The MAPE of the testing data showed that more training data improves the estimation of the permeability from 4 % to 2.57 % and also the risk of overfitting is reduced. Using the simulation data multiple times (different time steps were taken), the MAPE of the testing data can be further decreased to around 1 %. After 5000 training epochs no improvement in the training is observable.

The numerical validation was done in the second step, to check which output variant gives a better estimation and how many time steps are necessary as input data. Both output variants give a good prediction. The one-node variant had a slightly better performance during the validation with numerical data. The MAPE of the validation data is only slightly influenced by the number of input nodes (number of evaluated time steps). With two or more (up to 20) time steps, the validation MAPE was always around 4 %. The MAPE for only one time step was above 10 %. As a default 10 time steps were chosen.

The experimental validation was done by comparing the experimental measurement with simulations, which used the estimated permeability values of the ANN. The comparison of the flow fronts for two experiments is exemplarily shown in figure 2. If the permeability values and the anisotropy of the tensor are within the training data range (figure 2A), the estimation of the ANN is good. If one of the values is outside the predefined training data range, the prediction gets worse (figure 2B). In such cases the three-node variant shows a more robust behavior, because this ANN has implicitly learned the correlation between the permeability values.

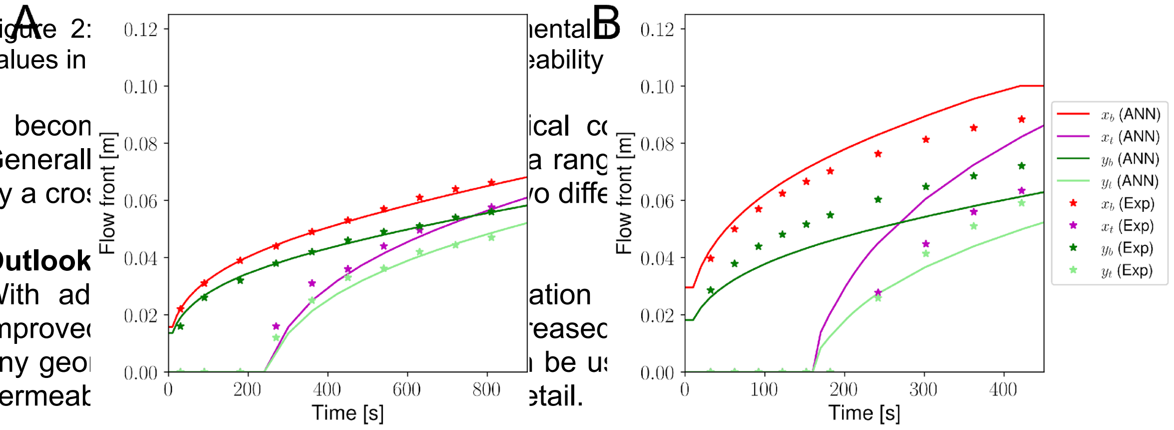


Figure 2: nental y
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